Zero-shot classification of ECG signals using a CLIP-based model

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Abstract

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# Introduction

According to the World Heart Federation (WHF), a leader in global cardiovascular health, among other reports from leading clinicians, researchers and institutions, cardiovascular diseases (CVDs) are a leading cause of mortality worldwide [17; 22; 25; 36]. In the United States, the Center for Disease Control (CDC) estimates that the annual total cost associated with CVD-related treatment and mortality is approximately $219 billion dollars (USD) per year [18; 21]. Given the financial and socioeconomic burdens of CVDs, it is essential that individuals receive timely and accurate medical care for the diagnosis, treatment, and ongoing care of CVDs.

An electrocardiogram (ECG) remains the medical standard and benchmark for the identification and diagnosis of CVDs with more than 300 million ECGs being performed globally [7]. In general, ECGs measure the changes in electrical membrane potential of the heart across different directions of the body and are often referred to as leads with a 12-lead ECG report being the most common type of report [14; 29]. Once an ECG report is available, it is ready to be analyzed by a licensed medical professional such as a cardiologist or an auxiliary medical professional.

However, it is important to note that even today, interpreting and analyzing ECG reports remains a highly complex and time-consuming process for medical professionals [11]. Not only are ECG reports manually annotated but the individual analyzing the ECG report must possess a high degree of technical skills and a vast understanding of topics such as cardiac anatomy, electrophysiology, pattern recognition, coronary distribution, and pathophysiology to perform correctly and accurately [11]. In one systematic literature review by Cook et al., it was found that medical professionals, such as cardiologists, across levels of education experienced challenges in providing a correct diagnosis for an ECG report with correct interpretation accuracy ranging from 49% to 92% and with a median interpretation accuracy of 57% [11]. In the same systematic literature review, it was also found that medical professionals who received continuing education and training related to ECG interpretation and analysis, did improve their ability to correctly provide a diagnosis for an ECG report with a median accuracy of 67%, suggesting that ongoing training for medical professions can play an important role in providing correct diagnoses [11].

Seeing the challenge that medical professionals faced with ECG interpretation, many computer scientists and physicians aimed to address this problem. Namely, with the numerous advancements observed in machine learning (ML), deep learning (DL), and artificial intelligence (AI) vision models over recent years, it was postulated and believed that using ML and DL vision models may be able to correctly classify pathologies related to ECG reports [citation needed].

In this paper, our goal is to build upon and contribute to the body of work of DL literature as it relates ECG classification. Particularly, in this study, we demonstrate that using a multimodal Contrastive language image pre-training (CLIP) framework is effective in the diagnoses of any number and combination of ECG diagnostic classes. After conducting a thorough literature search and review, it is to the best of our knowledge that using a multimodal CLIP framework within the field of ECG classification has not yet been explored extensively with a only handful of studies related to this topic being published within the last two years. Overall, we show that…. [To be continued upon results]

In the next section, Related Works, an overview of CLIP and the current state of ML & DL models for ECG classification will be provided. In addition, the topic of Zero-shot classification as it relates to our study will also be discussed.

# Related Works

## Contrastive language image pre-training (CLIP)

In 2021, OpenAI researchers published their paper, “Learning Transferable Visual Models From Natural Language Supervision” which introduced a novel approach to multimodal learning, namely, Contrastive language image pre-training or CLIP for short [10; 20]. CLIP is a multimodal framework that comprises of two components, an image encoder (vision model) and a text encoder (text model) [10; 20]. When using a CLIP framework, the image encoder is trained alongside the accompanying text encoder [10]. This allows the CLIP-based model to develop a comprehensive or "deep" understanding of its image-text pair inputs [20]. To facilitate the learning process, the CLIP framework utilizes contrastive loss (also known as symmetric loss) [10; 20]. Contrastive loss calculates the distance between the embeddings of the image-text pair inputs and aims to minimize the overall distance between image-text pairs when one sample is like another (positive instance) and maximize the distance between image-text pairs inputs when samples are not similar to other samples (negative instance) [10; 20]. In doing this, the two text and image encoders are incentivized to learn better representations of their inputs to capture the semantic relationship between embeddings of image-text pairs and are penalized when they do not learn or capture reliable representations of the image-text pairs [20].

Unlike traditional ML or DL approaches for classification tasks, which are generally jointly trained with some image feature extractor and a classifier to predict the corresponding image class or label(s), the notion of using a CLIP-based model presents a novel approach for classification tasks [20]. With a CLIP-based model, the model can be utilized for zero-shot classification across a variety of classification tasks and for many types of datasets. In our study, we demonstrate that a CLIP-based model can be used within zero-shot learning (pending).

Task 1: Put Image of Contrastive Learning Pseudocode or type in LaTex and insert equations

## Related Works – Deep Learning and ECG Classification

In the fields of AI, ML, and DL, the primary goal has been to create models capable of correctly classifying CVDs from ECG reports [2]. To achieve models capable of this, a patient’s medical history including their ECG report(s) are aggregated, preprocessed, and then analyzed by the model which in the end, provides a recommendation or classification based on its input.

In the past decade, several notable ECG classification models have been developed that have demonstrated to be as effective in correctly classifying CVDs from ECGs as experienced cardiologists using ECG signal inputs [4; 23]. In one systematic literature review about state-of-the-art (SOTA) DL methods for ECG classification by Petmezas and colleagues, it was found that the most popular DL models for ECG classification tasks included variants of convolutional neural networks (CNNs), recurrent neural networks (RNNs), ResNet models, and LSTM models [33]. From the studies reviewed in this systematic review, 66.1% favored using CNNs for specific, downstream ECG classification tasks [33]. In Lu et al.’s study, the researchers achieved an accuracy of 99.31% for arrhythmia classification using a 1D-CNN [19; 33]. In a different study, authors Yu et al. achieved an accuracy of 99.70 % for premature ventricular contraction also utilizing a 1D-CNN demonstrating the robustness of CNNs for different types of, singular-class of ECG classification tasks [6; 33]. Other studies have also demonstrated that training and using CNNs is effective for CVD classification tasks for classes such as myocardial infarction, coronary artery disease, and congestive heart failure to name a few.

While these models do perform well in isolated conditions where they are trained to

## Related Works – Zero-shot Learning

# Materials and Methodology

## 3.1 Experiment A

## 3.2 Experiment B

# Results

# Discussion

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